Sensor Fault Diagnosis and Reconstruction of Engine Control System Based on Autoassociative Neural Network

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Abstract: The topology and property of Autoassociative Neural Networks (AANN) and the AANN's application to sensor fault diagnosis and reconstruction of engine control system are studied. The key feature of AANN is feature extract and noise filtering. Sensor fault detection is accomplished by integrating the optimal estimation and fault detection logic. Digital simulation shows that the scheme can detect hard and soft failures of sensors at the absence of models for engines which have performance deteriorate in the service life, and can provide good analytical redundancy.

Key words: Autoassociative Neural Network; engine sensor; fault diagnosis; analytical redundancy

基于自联想神经网络的发动机控制系统传感器故障诊断与重构. 黄向华. 中国航空学报(英文版), 2004, 17(1): 23-27.

摘 要: 研究自联想神经网络及其在发动机控制系统传感器故障诊断及重构中的应用。自联想神经网络关键在于特征提取和噪声滤波。综合自联想网络的最优估计与故障诊断, 自动区分估计误差和传感器故障。仿真结果表明这种方法不需要模型, 能诊断传感器硬、软故障, 当发动机性能蜕化时也能提供很好的解析余度。

关键词: 自联想网络; 发动机传感器; 故障诊断; 解析余度
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Sensor fault diagnosis and reconstruction are required to achieve adequate reliability in engine control system. Robustness requirement offers challenges to the design of a fault diagnosis system. The approach using intelligent algorithms is a promising one[1]. For a sensor set which has redundant information, it is possible to reconstruct one or more lost sensor data if the relationship among the sensors is known. Usually, the relationship can be described as mathematical equations with sensor measurements as input variables. The method provided in this paper is based on Autoassociative Neural Network (AANN) and can realize the relationship and reconstruct failed sensors.

1 Topology Architecture of AANN[2,3]

Nonlinear Principal Component Analysis (NLPCA) is the basis of AANN. NLPCA is a technique for mapping nonlinear multidimensional data into lower dimensions with minimal loss of information. Let $\boldsymbol{Y}=[y_1 \quad y_2 \quad \cdots \quad y_m]$ represent a $n \times m$ table of data (n = number of observations, m = number of variables). The mapping into feature space can be represented by

$$\boldsymbol{T} = \boldsymbol{G}(\boldsymbol{Y}) \qquad (1)$$

where $\boldsymbol{T}=[t_1 \quad t_2 \quad \cdots \quad t_f]$ is the principal component matrix ($n \times f$); f is the number of principal components ($f < m$); $\boldsymbol{G}$ is a nonlinear vector function. Restoring the original dimensionality of the data is implemented by another nonlinear vector function

$$\boldsymbol{Y}' = \boldsymbol{H}(\boldsymbol{T}) \qquad (2)$$

The loss of information is measured by residual $\boldsymbol{E} = \boldsymbol{Y} - \boldsymbol{Y}'$, and $\boldsymbol{E}$ consists of minor components which involve noise or unimportant variance. Functions $\boldsymbol{G}$ and $\boldsymbol{H}$ are selected to minimize $\|\boldsymbol{E}\|$ in order to draw principal components.

Function $\boldsymbol{G}$ and $\boldsymbol{H}$ can be represented by 2

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feedforward neural network(NN) with one hidden layer. The combined network, which is called AANN, can produce the identity mapping, $\boldsymbol{Y} \to \boldsymbol{Y}'$, as shown in Fig. 1. AANN contains three hidden layers: mapping layer, bottleneck layer and demapping layer. $\boldsymbol{Y}'$ is the output of AANN, which is the filtered input, and has the same dimension as input $\boldsymbol{Y}$. Original data are compressed to the lower dimension feature space by input layer, mapping layer and bottleneck layer, and then the outputs of feature space are mapped to output layer through bottleneck layer, demapping layer and output layer, and reconstruct the input data. The weights $\boldsymbol{W}$ and biases $\boldsymbol{B}$ of the AANN are optimized in order to reserve the information of input data in bottleneck layer entirely.

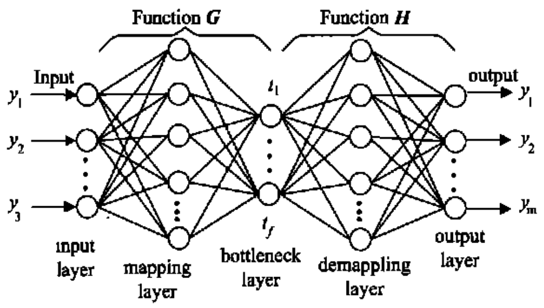

Fig. 1 Topology architecture of AANN

The key point of an AANN is the bottleneck layer, whose nodes are the smallest in dimension. The bottleneck forces an internal encoding and compression of the input, with a subsequent decoding and decompression after the bottleneck, and the network output is produced. The bottleneck layer prevents the network from a simple one-to-one or "straight-through" mapping during training the network. Internal restricted fact is included in the bottleneck layer of AANN, which can make AANN learn the internal relationship between all inputs rather than simple unit function. AANN realizes NLPCA, whereas normal feedforward NN can not extract feature and reconstruct data because it has no the ability of coding and decoding.

AANN has the property of noise filtering, which depends on the ability of the network to produce a model of the measurements that fits the systematic correlations in the data, yet excludes random variations due to measurement noise. Noise filtering in AANN also depends on redundancy. Redundancy reduces variance in the similar way as that using samples containing multiple items reduces variance in statistical quality control.

2 Selection of Network Nodes

In the combined network, there are m nodes in the input and output layers and f nodes in the bottleneck layer. The number of mapping and demapping nodes (M_1 and M_2) must be selected properly in order to ensure adequate representational capacity without overfitting[2]: $M_1 + M_2 \ll n$, where n is the number of observations. Cross-validation[4] (training on a subset of the training examples, reserving other examples for testing generalization ability) can also be used to select an appropriate number of mapping and demapping nodes, and to limit the intensity of training.

For aircraft engine, self-relationship can be drawn from the thermodynamics and pneumatics relation among different measurements, and then the relationship among all variables can be decided, and the number of independent variables can also be decided, and also the number of bottleneck nodes. For those nonlinear objects the relationship of which is very complicated, since it is difficult to obtain their mathematical models, the self-relationship can be determined by analysis of the covariance matrix of the training set. For a set of m measured variables, the covariant matrix $\boldsymbol{R} = [r_{ij}]_{m\times m}$ is defined as

$$r_{ij} = \begin{cases} 1 & i = j \\ \dfrac{\mathrm{cov}(x_i, x_j)}{\sqrt{\mathrm{var}(x_i)\mathrm{var}(x_j)}} & i \neq j \end{cases} \tag{3}$$

where r_{ij} reflects the dependent relation between x_i and x_j. If an element r_{ij} in the covariance matrix is zero (or statistically indistinguishable from zero), then the corresponding measurements x_i and x_j are independent. Rearrange $\boldsymbol{R}$ in block diagonal form by re-ordering the measured variable results in a matrix that reveals the dependency structure of the measurements. Each square block of nonzero elements in $\boldsymbol{R}$ represents a set of mutually-correlated variables. A block (or set of blocks) not sharing variables with other blocks indicates the independence of the variables in the block (or set of blocks) from the remaining variables and can not introduce two independent groups of variables into a single AANN. Overlapping sets of blocks represent a subsystem of related variables. The number of blocks in an overlapping set of blocks is a lower bound on the number of independent variables (bottleneck nodes).

3 Sensor Fault Detection and Reconstruction Based on AANN

When network is trained abundantly, it can be used for sensor fault detection because there exists redundant information among input variables and when a sensor fails or even several sensors fail, the other sensors can still provide good estimation to replace the failed sensor. Estimation Returning Scheme (ERS) is developed to diagnosis sensor fault, by comparing the output of network and the corresponding sensor output to detect sensor faults. If the difference between a sensor measurement and its estimation exceeds the threshold while the differences of other sensors with their corresponding estimation (*e. g.* relatively low), then a sensor fault is declared to happen. Once a faulty sensor measurement is detected, it will be disconnected from the input layer of network. However, the neural network will continue to function by using the most recent corresponding output of the NN as input instead of the faulty sensor measurement, because the most recent output is a good estimation of the faulty sensor measurement when there are enough information on input variables. And AANN has the ability of fault tolerance for the fact that the disturbance from input nodes can be distributed to the network and has little impact on output. The controller will be switched to the estimated value to continue the system operation. Under this scheme, the system can remain operable even with multiple sensors faults as long as normal sensors are not less than bottleneck nodes. The ability to combine detection, isolation and accommodation in one step is the key advantage of AANN based sensor validation scheme. This ability is based on the dimensionality reduction property of AANN.

There will be performance degeneration or installation and manufacture tolerance which are the sources of uncertainties and will cause estimation error in the optimal estimation of AANN. These uncertainties may be taken for sensor fault or vice verse. If the degeneration is taken for sensor fault, fault will be wrongly warned, causing incorrect fault accommodation. And if sensor fault is taken for degeneration, it will cause incorrect network compensation. Fault control gain together with soft fault detection logic[5] is developed to distinguish optimal estimation error from sensor faults in this paper. Axial directional fault signature is used to identify the cause of optimal estimation error. If the residual is caused by optimal estimation error, then the weights and biases of AANN will be compensated on-line. If the residual is caused by sensor fault, then corresponding estimation is used to replace the failed sensor, providing analytical redundancy. In the fault accommodation logic the fault control gains are used to provide a smooth transition from the failing sensor to its corresponding estimation.

4 Example of Digital Simulation

Let's take a turboshaft engine for example[5]. Fig. 2 shows the closed loop control system of a engine system consisting of the engine, controller and AANN-based sensor fault diagnosis. The primary variables of interest are, n_g, n_p, T_{t45}, P_{s3}, M_l and W_{fB} n_{p_g} is the given speed of power turbine, and M_l and n_{pg} are inputs. The control feedback variables are n_g, n_p, T_{t45}, P_{s3}.

Only when the input variables of AANN are correlative, the valid feature of the variables can be extraced from the bottleneck layer. The covariance matrix of 6 variables, n_g, n_p, T_{t45}, P_{s3}, W_{fB}, M_l can reflex the correlation:

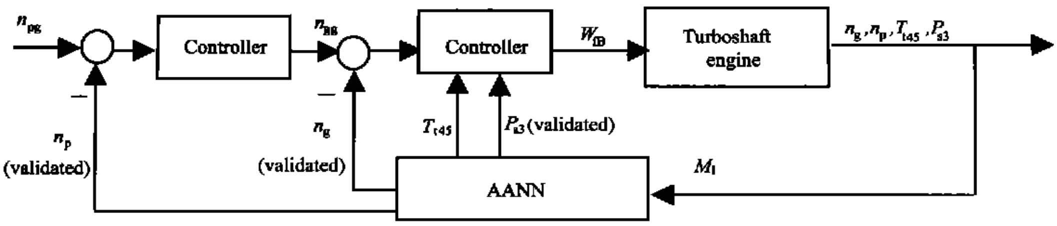

Fig. 2 Close-loop control system of a turboshaft engine

$$
\boldsymbol{R} = \begin{array}{c}
\begin{array}{cccccc} n_g & T_{t45} & P_{s3} & W_{fB} & n_p & M_1 \end{array} \\
\left[\begin{array}{cccccc}
1.00 & 0.99 & 1.00 & 0.97 & 0.87 & -0.19 \\
0.99 & 1.00 & 0.99 & 0.97 & 0.90 & -0.21 \\
1.00 & 0.99 & 1.00 & 0.98 & 0.85 & -0.16 \\
0.97 & 0.97 & 0.98 & 1.00 & 0.80 & -0.05 \\
0.87 & 0.90 & 0.85 & 0.81 & 1.00 & -0.54 \\
-0.19 & -0.21 & -0.16 & -0.05 & -0.54 & 1.00
\end{array}\right]
\end{array}
\begin{array}{c} n_g \\ T_{t45} \\ P_{s3} \\ W_{fB} \\ n_p \\ M_1 \end{array}
$$

When $|R_{ij}| < 0.4$ in the covariance matrix $\boldsymbol{R}$, the ith and jth variables are considered uncorrelated. As discussed above, 2 nodes are selected in bottleneck layer.

Using cross validation theory, AANN is trained with mapping nodes of 8-16 respectively. The smallest error estimate $E(\mathscr{A}, \mathscr{D})$[4] is obtained when the number of mapping nodes is 12.

When a sensor fault is declared, it is cut off from the input of AANN. The input of network is then replaced by the last estimation of the sensor, and the network can still works well. ERS is adopted to detect sensor faults for the real-time requirement. Considering the robustness to uncertainty, AANN is trained with normal data and compensated on-line. The procedure of sensor fault diagnosis and reconstruction of engine control system based on AANN is

(1) Collect data from test or simulation and use normal data to train AANN off-line. Relative variables are adopted in this paper.

(2) Adopt synthesis logic of optimal estimation and fault detection to distinguish whether the residual is from sensor fault, gas path fault or estimation error. Measurements such as speed, flow, temperature and pressure will vary because of the gas turbine engine component faults or performance degeneration. Gas path analysis, which calculate the fault coefficient matrix[6], can distinguish them from sensor failures. An axial directional fault signature of sensor fault occurs whenever one component of the error vector becomes large and all the other vector components remain small.

(3) If difference is caused by performance degeneration, then AANN is compensated on-line until the difference is eliminated.

(4) If the difference is caused by sensor fault, then the failed sensor is cut off and replaced with the estimation of network.

In this example, the training set is comprised of 84 points at various power levels, Mach numbers and altitudes which include various steady state operating points. Zero mean and normal distributed noise is added to the training data for input(not the target values) to make the network learn the correlation among the data. Also the loop is restarted several times during the training to use different noise values in each time and to change the order of the data in the training set to avoid learning any geometries that would occur due to the specific location of the data in the training set.

Fig. 3 is the result of soft fault detection of engine. The soft fault is initiated by setting n_g sensor output increasing slowly at speed of 0.5% per second. Fault signature and 3-level threshold (maximum tolerance(M_T), isolation threshold (I_T) and fault threshold(F_T)) are adopted to detect sensor faults. There may be a soft fault of n_g sensor or performance degeneration occurring when the fault control gain g_{n_g} is larger than 0 at the 3 second. When the error between evaluation and sensor output is larger than I_T(330r/min), a probable fault is isolated. When the error is larger than F_T (1350r/min), the fault control gain is 1 and the

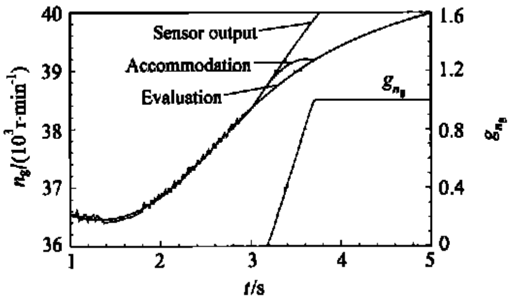

Fig. 3 Soft fault detection of AANN

fault control gains of other sensors remain small, a fault is declared to be detected. The residual will become small again when the sensor fault is successfully detected and accommodated. When the error is larger than I_T and less than F_T, fault control gain and accommodation are

$$g_i = \begin{cases} 0 & |e_i| \leqslant I_{T_i} \\ \dfrac{|e_i| - I_{T_i}}{F_{T_i} - I_{T_i}} & I_{T_i} < |e_i| < F_{T_i} \\ 1 & |e_i| \geqslant F_{T_i} \end{cases}$$

$$n_g = (1 - g_{n_g}) n_{gs} + g_{n_g} n_{g_e}$$

where n_{g_e} is n_g evaluation of AANN. When a fault is declared, accommodation goes smoothly from sensor output to network estimation. In the whole process, in spite of the deviation of sensor output and ANN evaluation, the n_g accommodation value which will be used by controller deviates little, so the engine can operate normally.

5 Conclusion

ANN is a kind of feedforward neural network which has special topology architecture. It has excellent capability of feature extraction and noise filtering. An example of sensor fault detection and reconstruction of engine control system using AANN is presented. Simulation results show that analytical redundancy based on AANN uses only engine sensor outputs to train AANN and does not need engine model. The integrated logic of optimal estimation of ANN and sensor fault diagnosis is developed to distinguish optimal estimation error from sensor faults. This logic can avoid the problem of ANN damaged by sensor failure, and also can avoid the problem of false diagnosis by estimation error. Control system will work normally even there are sensor faults.

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